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Nowcasting Real GDP growth in South Africa*

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Abstract

This paper uses nowcasting to forecast real GDP growth in South Africa from 2010Q1 to 2014Q3 in real time. Such an approach exploits the flow of high-frequency information underlying the state of the economy. It overcomes one of the major challenges faced by forecasters, policymakers, and economic agents - having a clear view of the state of the economy in real time. This is often not the case as many economic variables are only available at low frequency and with considerable lags, making it difficult to have information on the state of the economy even after the end of the quarter. The pseudo out-of-sample forecasts show that the nowcasting model's performance is comparable to those of professional forecasters even though the latter enhance their forecasting accuracy with judgement. The nowcast model also outperforms all other benchmark models by a significant margin.

JEL Classification Numbers: *E52; C53; C33.*

Keywords: Nowcasting, Factor Model, Bayesian VAR, Forecasting.

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Non-technical summary

A common problem policymakers, economists and forecasters face is the lack of essential economic data in real time. The information needed is often only available at lower frequencies and published with a considerable lag. This is the case with real gross domestic product (GDP), which is the single most relevant variable describing the path of the economy. GDP is used, together with inflation, to substantiate the direction of monetary policy. However the delay in GDP releases makes it difficult to predict the current state of the economy with accuracy. One way to improve this accuracy is to use higher frequency economic information more readily available in real time. Although some forecasters use judgement to incorporate higher frequency data into their forecasts, most models cannot incorporate this data because of three common challenges. First, higher frequency data are not released in a synchronous fashion, which means there tend to be gaps towards the ends of the sample. Second, information is not released at the same frequency; a quarterly projection model cannot use daily data. Finally, most traditional econometric models are unable to accommodate a large set of information.

This study addresses these forecasting challenges using a nowcasting model proposed by Giannone, Reichlin, and Small (2008). We adapt this model to the South African economy over the period 2005 to 2014. The framework uses daily, monthly, and quarterly data to forecast real GDP exploiting information in a data-rich environment. This leads to two major advantages: it incorporates a large information set and it permits disaggregation of the growth drivers to aid analysis of the forecast. For example, we can link recent movements in variables such as the Purchasing Managers' Index (PMI) and consumer confidence directly to our expectation of real GDP growth providing a continually updated real-time view of the economy.

We compare the performance of our nowcasting model to consensus forecasts by Reuters and Bloomberg as well as to seven alternative models: a random walk model, two autoregressive (AR) models, two small-scale vector autoregressive (VAR) models, and two large-scale VAR models. The results show that the nowcasting model performs comparably to consensus forecasts despite not incorporating judgement as is the case with survey forecasts.[1] Although our model does not include judgement, a valuable by-product of the nowcasting model is that the statistical methods can highlight potential anomalies. Thus through disaggregating growth drivers it can assist forecasters to use ex post judgement in assessing the severity of the anomaly. Importantly, the nowcast model also outperforms all other alternative models by a significant margin.

[1] There is a useful role for judgement in short-term forecasting, as forecasters are likely to be aware of conditions that are not always captured by available data.

1 Introduction

One of the major challenges facing forecasters, policymakers, and economic agents is having a clear view of the state of the economy in real time. As real gross domestic product (GDP) is only available at quarterly frequency and with a significant delay, it is difficult to have information on the state of the economy even after the particular quarter has passed. For example, the fourth quarter GDP figure for South Africa only becomes available eight weeks after the end of the quarter. This obstructs analysis and thus policy decisions, both of which require real-time information. However, a substantial amount of higher frequency economic information is released between the start of the quarter and the release of the official GDP figure. Although rarely exploited in growth models, these high frequency data can help predict the current state of the economy, the near future, and near past. This is done using nowcasting.

Nowcasting, as introduced by Giannone, Reichlin, and Small (2008), provides a framework for the integration of a large number of timely economic series that matter for economic growth in a mixed frequency and asynchronised environment. The prediction of the current state of the economy is known as *nowcast* and the prediction of the near past as *backcast*. Such statistical models outperform a naïve constant growth model in forecasting GDP growth at very short horizons, i.e. the current state and the near future; however, they perform more poorly in the medium to long term (Giannone, Reichlin, and Small, 2008; Banbura, Giannone, and Reichlin, 2011; Banbura, Giannone, Modugno, and Reichlin, 2012).

So far there has been few attempts at estimating a nowcast model in Africa, let alone for South Africa. This paper bridges the gap in the literature by estimating a nowcast model of real GDP growth in South Africa. It uses 21 indicators covering the real economy, nominal variables, and the financial sector. Like most nowcasting models, the dataset contains variables published at different frequencies: daily, monthly, and quarterly. Furthermore, information flows are asynchronous resulting in missing data toward the end of the sample with the forecasting exercise performed on the 15th of each month. The sample period is from 2005 to 2014, while the pseudo out-of-sample period is from 2010Q1 to 2014Q3.

We compare the performance of our nowcasting model to consensus forecasts by Reuters and Bloomberg as well as to seven alternative models. The nowcasting model performs similarly to consensus forecasts despite the atheoretic nature of the nowcast approach. In contrast to the survey forecasts, our model does not incorporate judgement. This becomes evident when we consider the first quarter of 2014 when a prolonged strike in the platinum sector resulted in a contraction in real GDP growth. However, this does not mean judgement can't be incorporated after the model has evaluated the data. In fact, the model helps disaggregate the drivers of growth assisting the forecaster to apply judgement if needs be. The seven alternative models comprise of a random walk model, two autoregressive (AR) models, two small-scale vector autoregressive (VAR) models, and two large-scale VAR models. Importantly, the nowcast model outperforms all of these models by a significant margin.

The rest of the paper is organised as follows: Section 2 describes the literature and methodological issues around nowcasting. Section 3 describes the nowcast model. We discuss the data used in Section 4. In addition, we discuss the approach used to select the factors and their identification. Section 5 discusses the results of pseudo out-of-sample forecasting. Section 6 provides some concluding remarks.

2 Literature Review

Giannone, Reichlin, and Small (2008) propose an approach that uses factor analysis in a data-rich environment together with the Kalman filter as a comprehensive and powerful technique for forecasting the near past, the current state, and the near future of GDP growth rate in the US. There are important findings from their analysis. First, the nowcast model outperforms the naïve constant growth model over the short-run, especially for the current quarter. Second, the proposed model performs equally well as the professional forecasts, despite the fact that the latter includes judgement. Third, as one would intuitively expect, the performance of the nowcast model improves as new information becomes available and towards the end of the quarter. This means that the forecaster can incorporate information progressively upon its release and increase their understanding of the drivers of GDP growth. Finally, it is not necessarily the strength of the relationship between each variable and GDP which matters, but rather the timeliness of each variable. For example, when Purchasing Managers' Index (PMI) is released at the beginning of each month, there is no hard data available. In addition, the Bureau of Economic Research (BER) and the South African Chamber of Commerce and Industry (SACCI) confidence indices of the corresponding quarter are published respectively four and two weeks before the end of the quarter. It implies that soft data are extremely important (see Kabundi, 2004 and Martinsen et al., 2014).

Since the seminal work by Giannone, Reichlin, and Small (2008) there has been an increase in popularity of these models for predicting different macroeconomic variables and in different countries. This methodology has since been introduced in various central banks such as the Federal Reserve Bank of Atlanta (2014) and the European Central Bank (2008). There are also several applications in different countries.[2] Additionally,

[2] Kuzin, Marcellino, and Schumacher (2013) use model combination in nowcasting the German GDP,

since the model is purely data-driven it allows an array of innovative practices. Instead of using key determinants of GDP, Angelini, Banbura, and Runstler (2010) forecast different components of GDP, and then aggregate them to obtain a nowcast of GDP. Another variation of the technique is Liebermann (2012), who provides a detailed study on the nowcasting of a large variety of key monthly macroeconomic releases, while Modugno (2013) uses the same framework for forecasting inflation.

Nowcasting ensures flexibility by overcoming three common challenges. First, given that data is released in different frequencies, the forecaster needs to reconcile the data into a single frequency. For example, manufacturing production, which is closely related to GDP, is published monthly. The problem of mixed-frequency is easily translated to a task of missing data. Traditionally, forecasters use bridge equations as means of reconciling mixed-frequency information. However, such a solution is suboptimal, as bridge equations are single regression models that can only accommodate few variables.

Second, data are not released in a synchronous fashion. For example, the PMI for February is published at the beginning of March, while the exports and imports for February become available at the end of March. Similar to the mixed-frequency problem, the unbalanced panel at the end of the period is also looked at as a missing-data question. One way of solving this problem is to move all series later in order to have a balanced panel at the end of the period. The drawback of such approach is one does not take into account the true contemporaneous correlation that exists among variables at each period introducing a lead-lag relationship between variables. Evans (2005) and Giannone, Reichlin, and Small (2008) propose the use of the Kalman filter as a solution to this problem, given its ability to adapt to changing data availability.

This leads to the third challenge - most traditional models are unable to accommodate a large set of information. Nowcasting overcomes the curse of dimensionality (large number of parameters relative to the number of observations) by summarizing information using a dynamic factor model. Meaning that forecasters benefit from a rich information set. Forni, Hallin, Lippi, and Reichlin (2003) and Stock and Watson (2003) demonstrated that factor models turn the curse of dimensionality into a blessing

Matheson (2010) nowcasts New Zealand GDP and CPI, Yiu and Chow (2011) and Giannone, Agrippino, and Modugno (2013) use it for China, Aastveit and Trovik (2008) build a nowcast model for Norway, Siliverstovs and Kholodilin (2010) apply the same approach for Switzerland, D'Agostino, McQuinn, and O'Brien (2008) for Ireland, Barhoumi, Darn and Ferrara (2010) nowcast the French GDP growth, de Winter (2011) shows the superiority of this technique for the Netherlands, Arnostova, Havrlant, Ruzicka and Toth (2011) confirms the findings by other scholars for the Czech Republic, and for Brazil Bragoli, Metelli, and Modugno (2014) show that nowcasting performs as well as predictions of professional forecasters. Matheson (2011) tracks growth in 32 advanced and emerging-market economies with a nowcast.

of dimensionality.

3 The Nowcasting Model

The added advantage from nowcasting is its ability to use high frequency data (daily and monthly in our case) to estimate quarterly macroeconomic variables. Thus we estimate GDP in quarter q, $\hat{z}^q_{k|\theta_j}$, by using the information available during that quarter, denominated as Ω_{θ_j}. We estimate

$$\hat{z}^q_{k|\theta_j} = Proj[\hat{z}^q_{k|\Omega_j}] \tag{1}$$

As more information is released, this is integrated into the projection. Thus the forecast is made with the most up-to-date and comprehensive information set at each point in time such that

$$\Omega_{\theta_j} > \Omega_{\theta_{j-1}} > \Omega_{\theta_{j-2}} > ... \tag{2}$$

We estimate GDP using the dynamic factor model suggested by Doz, Giannone and Reichlin (2005). Since the frequency of the dataset differs, introducing missing data points, and the common factors are unobserved, we need to use the Kalman filter. The Kalman filter is a discrete, recursive linear filter used to estimate unobservable variables in a system of equations given an information set (Pasricha, 2006). The Kalman filter is optimal because it minimises the mean squared error estimator, if the observed variable and error are jointly Gaussian and is "best" in the class linear filters if this assumption is violated.

The factor, F_t, summarises the co-movements from the latest available information set. Thus we estimate the corresponding monthly GDP, $y_{t|\theta_j}$, to the quarterly series $\hat{z}^q_{k|\theta_j}$ by

$$y_{t|\theta_j} = \mu + \Lambda F_t + \epsilon_{t|\theta_j} \tag{3}$$

where μ is a constant, Λ is $r \times m$ coefficient matrix, $\epsilon_{t|\theta_j}$ is a white noise error, and F_t is the unobserved factor. We specify the common factors as VAR(1)

$$F_t = MF_{t-1} + N\mu_t \tag{4}$$

where M is a $r \times r$ matrix, N is a $r \times l$ matrix of full rank r and μ_t the common factor shocks.

As there can be more than one significant co-movement in the information set, there can be more than one factor needed in the model. We test the number of common factors using the modified Bai and Ng (2002) information criterion.[3] To determine the number of common factors, this method determines the factor which minimises the variance of the idiosyncratic component.[4]

Near-term forecasting rarely provides any insight to the marginal change in GDP. This is not the case with nowcasting. Since the model is purely data-driven it permits the breakdown of the marginal impact of specific variables on the GDP forecast, making it possible to analyse the drivers of the forecast. This ability is called the *News* of the model.

We estimate the *News* by

$$NEWS[z^q_{k|\theta_j}, \theta_j] = \hat{z}^q_{k|\theta_j} - \hat{z}^q_{k|\theta_{j-1}} \tag{5}$$

which is the difference between the forecast of GDP including $\hat{z}^q_{k|\theta_j}$ and excluding $\hat{z}^q_{k|\theta_{j-1}}$ the most recent datapoint of various variables used. Thus, indicating the impact of certain datapoints on GDP. This is a valuable function as the impact of recent releases can pinpoint latest developments in the economy and increase our understanding of the current state of the economy.

4 Alternative Models

We use five alternative models which serve to compare the performance of the nowcasting model. Unlike the nowcasting model which uses data in mixed-frequency domain, the alternative models use only quarterly variables. We use a combination of univariate and multivariate models. The univariate models include the random walk (RW) model and the autoregressive model of the form

$$Y_t = B_0 + B_1 Y_{t-1} + B_2 Y_{t-2} + ... + B_p Y_{t-p} + \nu_t \tag{6}$$

where ν_t is the error term. Equation 6 is a RW with drift when $B_1 = 1, B_0 \neq 0$, and the coefficients of other lags are set to zero. However, if $B_0 = 0$, the model is RW without drift. Equation 6 is an autoregressive process of order p when the coefficients of $Y_{t-1}, Y_{t-2}, ..., Y_{t-p}$ are different from zero. The paper uses two autoregressive models, namely, AR(1) and AR(4). If Y_t is a vector, Equation 6 becomes a multivariate model known as Vector Autoregressive (VAR) model. The estimation procedure includes four VAR models, two small-scale VARs and two large-scale VARs. The small-scale VARs contain four variables, namely, GDP growth, CPI inflation, the repo rate, and the nominal effect exchange rate. We use both VAR(1) and VAR(4) for small-scale VAR.

[3] As proposed by Alessi, Barigozzi and Capasso (2010).

[4] For more detail on the test specifications see Alessi, Barigozzi and Capasso (2010).

Given that the nowcasting model comprises 21 variables, it is appropriate to compare its forecasting performance with other large-scale models. But the traditional VAR models cannot accommodate such large number of variables without facing the degree-of-freedom issue, which in turn affects negatively the forecasting performance of the model. The main reason underlying poor performance of large VARs is the uncertainty concerning parameter estimation. Recently Gupta and Kabundi (2011) show that large-scale outperform small-scale models in forecasting GDP growth for South Africa. Thus, in addition to small-VARs we use a Factor-Augmented VAR (FAVAR) and a Large Bayesian VAR (LBAVAR) as alternative models. The FAVAR adds two common factors obtained from a panel of 17 of 21 variables included in the nowcasting model to four variables used in the small-scale VARs. The extracted factors summarise the information contained in the panel of 17 variables. Hence, instead of estimating a VAR with 21 variables, we estimate a VAR with six variables, four observed and two unobserved. The common factors are estimated using the VAR(1) as specified in Equation (3).

The LBVAR solves the problem of overparameterisation by shrinking parameters towards a parsimonious naïve random walk process using informative priors. Giannone, Lenza, and Primiceri (2015) demonstrate the superiority of these models in out-of-sample forecasting as they reduce the uncertainty associated with the estimation based flat priors when the number of variables increases significantly. However, the BVARs models are highly dependent on the choice of priors. Many empirical studies in economics use the Minnesota priors which shrink the parameters towards a random walk process.[5] The main issue with the Minnesota priors is the subjectivity it involves in the choice of priors. Instead this paper follows recent development by estimating prior hyperparameters as proposed by Giannone, Lenza, and Primiceri (2015). These authors treat these hyperparameters as additional parameters that need to be estimated.[6]

5 Data

The dataset contains 21 series covering real variables, nominal variables, and financial variables.[7] Giannone, Reichlin, and Small (2008) show that if variables are selected systematically including timely information concerning the current state of the economy, the cross-section need not to be very large. The real sector includes trade, production, and demand variables. The nominal variables are producer and consumer price indices,

[5] See for example Kadiyala and Karlsson (1997), Banbura, Giannone, and Reichlin (2010).

[6] We refer to Giannone, Lenza, and Primiceri (2015) for a technical explanation of LBVAR.

[7] Table 1 provides a complete list of variables. In addition, it shows the treatment, the source, the frequency, and the Bloomberg relevance of all variables.

and the Brent crude oil price (in US dollar). Financial variables are the nominal effective exchange rate and the policy rate (repurchase rate). Most series are expressed in log differenced at the monthly frequency.

Table 1: List of Variables

Variables	Sources	Frequency	Lag*	Relevance	Treatment**
Nominal Effective Exchange Rate	SARB	D	0		5
Kagiso Purchasing Manager Index	BER	M	1	70.27	1
Total Retail Trade Sales	STATS SA	M	44	64.86	5
Real Wholesale Trade Sales	STATS SA	M	46	0.00	5
Mining Production	STATS SA	M	44	27.73	5
Private Credit	SARB	M	29	51.35	1
Electricity Consumption	STATS SA	M	39	10.81	5
Motor Vehicle Sales	NAAMSA	M	2	32.43	5
SACCI Business Confidence	SACCI	M	3	54.05	5
Exports	SARS	M	31	94.59	5
Imports	SARS	M	31	94.59	5
Money Supply M3	SARB	M	29	78.38	5
Oil price - US dollar (Brent crude)	OECD	M	0		5
Trade Activity Index	SACCI	M	12		1
Trade Expectations Index	SACCI	M	12		1
Gold Production	STATS SA	M	44	50.00	5
Business Cycle Indicator	SARB	M	51	24.32	5
Consumer Price Index	STATS SA	M	20	72.97	5
Producer Price Index	STATS SA	M	30	78.13	5
Repo Rate	SARB	M	0	97.30	1
BER Consumer Confidence	BER	Q	-12	67.57	1
Capacity Utilisation	STATS SA	Q	67	0.00	1
Gross Domestic Product	STATS SA	Q	57	62.16	5

* Avergage number of days after the end of the observed period before that period's figure is released.

** 1 = no transformation, 5 = first difference of logarithm,

Quarterly series used are capacity utilisation, consumer confidence, and real GDP growth. These series are transformed into monthly frequency with quarterly values set as third month observations and missing data for the remaining two months of the quarter. Then, we use the Kalman filter to manage the missing data issue. The nominal effective exchange rate, the only variable obtained at daily frequency, is transformed to a monthly frequency by taking average of 15 days for each month since the pseudo real-time out-of-sample forecast exercise is conducted on the 15th of each month. All variables are transformed to induce stationarity. For professional forecasters, we use the forecasts based on the surveys conducted by Reuters published monthly, while the Bloomberg forecasts are released two days before the GDP release.[8]

The first task in nowcasting is the choice of variables to include. We use the view of market participants obtained from Bloomberg to decide on which variables to include.

[8] The mean of the Reuters survey is used.

Note that the policy rate matters more with a weight of 97.30, followed by trade balance with 94.59. Even though PMI seems less important than trade balance, it is timely, with only one day lag, while the latter is published with 31 days lag. Except for PMI and confidence indices, all variables are expressed as quarterly growth rate. In addition, we use annual growth for vehicles sales.

Table 2: Correlation coefficients

	GDP	PMI	Retail	Electricity	Vehicle	BCI	TEI
GDP	1						
PMI	0.80	1					
Retail	0.67	0.70	1				
Electricity	0.66	0.67	0.50	1			
Vehicle	0.58	0.62	0.59	0.50	1		
BCI	0.64	0.66	0.64	0.63	0.70	1	
TEI	0.67	0.76	0.65	0.71	0.68	0.65	1

Table 2 shows correlation coefficients between different variables. All variables are standardised to have the same unit of measurement. Most of the correlation coefficients are above 0.5, which is evidence that they move together. Importantly, they are highly correlated with GDP growth. PMI is the variable that mimics GDP growth quite closely. Even though, it is perceived as soft data, it is closely related to hard data and it is timely. Figure 1 shows how close PMI tracks GDP. It is incredible how PMI predicts turning points. It is mostly contemporaneous with GDP growth. It depicts a correlation coefficient of 0.8. This relatively high correlation is confirmed in Figure 1. In addition, Figure 2 confirms the observation in Table 2 about relatively strong correlation among real variables. It depicts evidence of strong co-movement with GDP growth which implies that they can serve as its determinants. Instead of choosing one variable over another, the model has the advantage of exploiting the data-rich information represented in Table 1. In contrast, traditional econometric models cannot accommodate all of these variables simultaneously in one model due to overfitting. Factor analysis can.

Figure 1: PMI and GDP growth

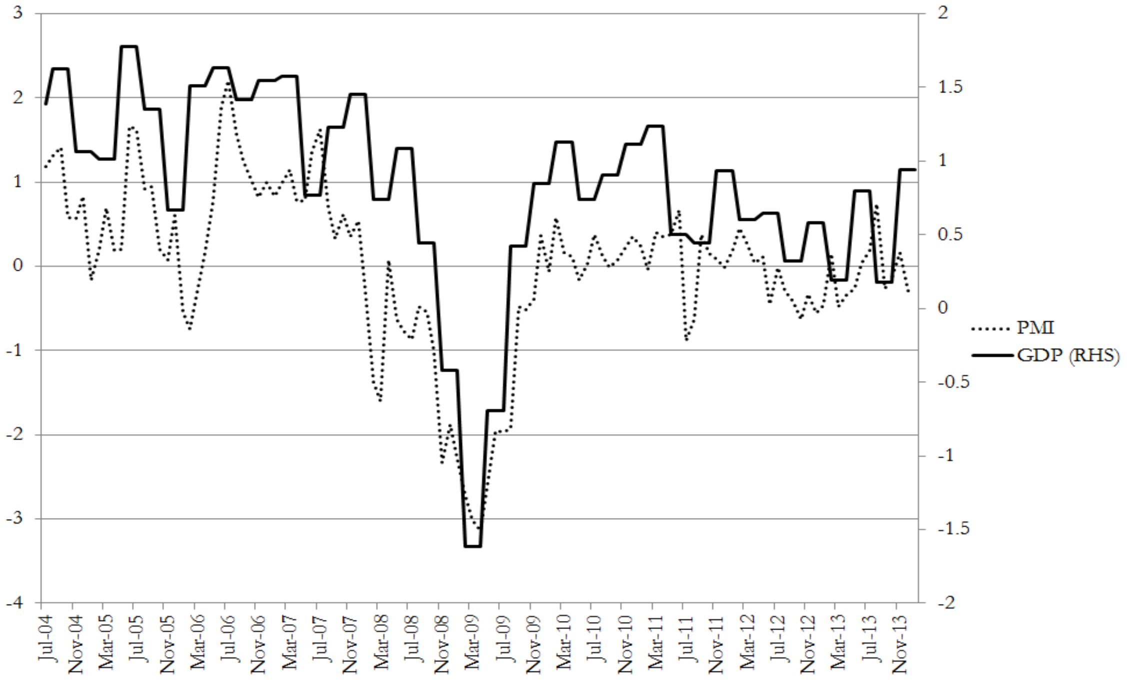
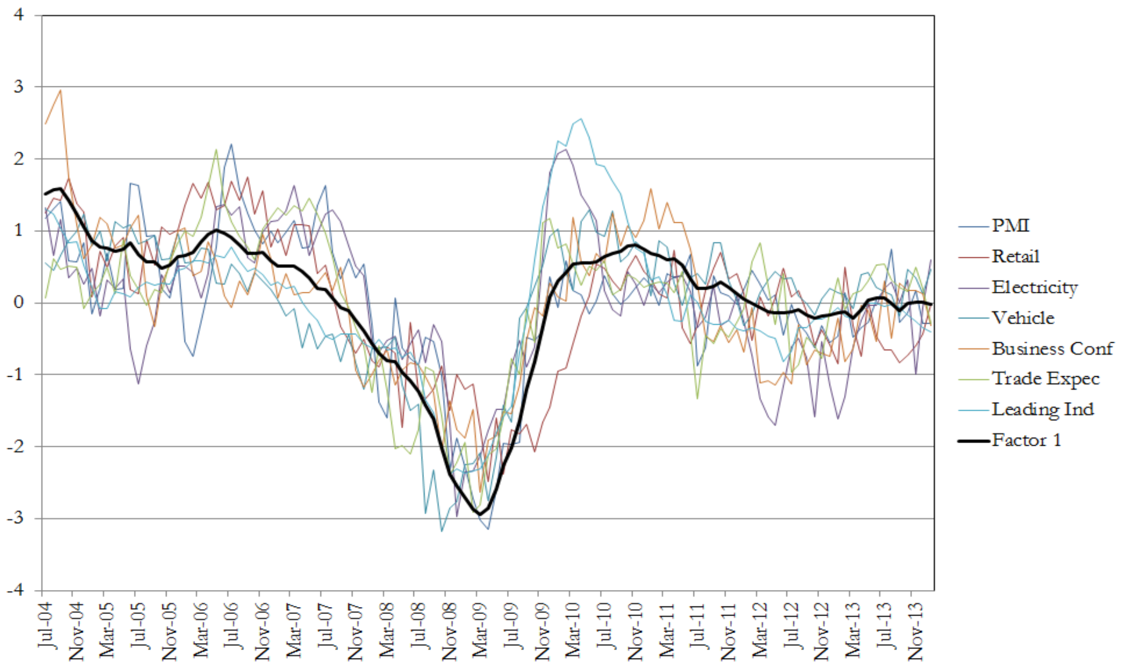


Figure 2: Real Variables and Factor 1



6 Empirical Results

We perform a pseudo real-time out-of-sample forecasting from the first quarter of 2010 to third quarter of 2014, using monthly and daily information from January 2005 to November 2014. We conduct the forecasting on the 15th of each month. The first task in nowcasting is to determine the number of factors to include. We use the Alessi, Barigozzi, and Capasso (2010) approach, an improvement of the most popular Bai and Ng (2002) methodology. We use one lag in the state equation for the estimation of factors. We compare our nowcasting model to both survey results as well as some benchmark models.

6.1 Determining the number of common factors and shocks

In order to determine the number of common factors to use in the model we implement a modified Bai and Ng (2002) information criterion as implemented by Alessi, Barigozzi and Capasso (2010). This method chooses the number of factors by minimising the variance of the idiosyncratic component of the approximate factor model. This is subject to a penalisation in order to avoid over-parameterisation. The information criterion is

$$\hat{r}^{T}_{c,N} = \underset{0 \leq k \leq r_{max}}{\operatorname{argmin}} IC^{T*}_{\alpha,N}(k) \tag{7}$$

where

$$IC^{T*}_{\alpha,N}(k) = log[\frac{1}{NT}\sum_{i=1}^{N}\sum_{i=1}^{T}(x_{it} - \hat{\gamma}_i^{(k)}\hat{F}_t^{(k)})^2] + ckp_a(N,T) \text{ for } a = 1,\ 2 \tag{8}$$

For k common factors, N is the number of variables, T the number of observations, $x_{it} - \hat{\gamma}_i^{(k)}\hat{F}_t^{(k)}$ the idiosyncratic error, c an arbitrary positive real number and $p_a(N,T)$ the penalty function.[9] Alessi et al. (2010) propose multiplying the penalty function by c since Hallin and Liska (2007) show that a penalty function, $p(N,T)$, leads to consistent estimation of $r < k$, the number of factors, if and only if $cp(N,T)$ does as well.

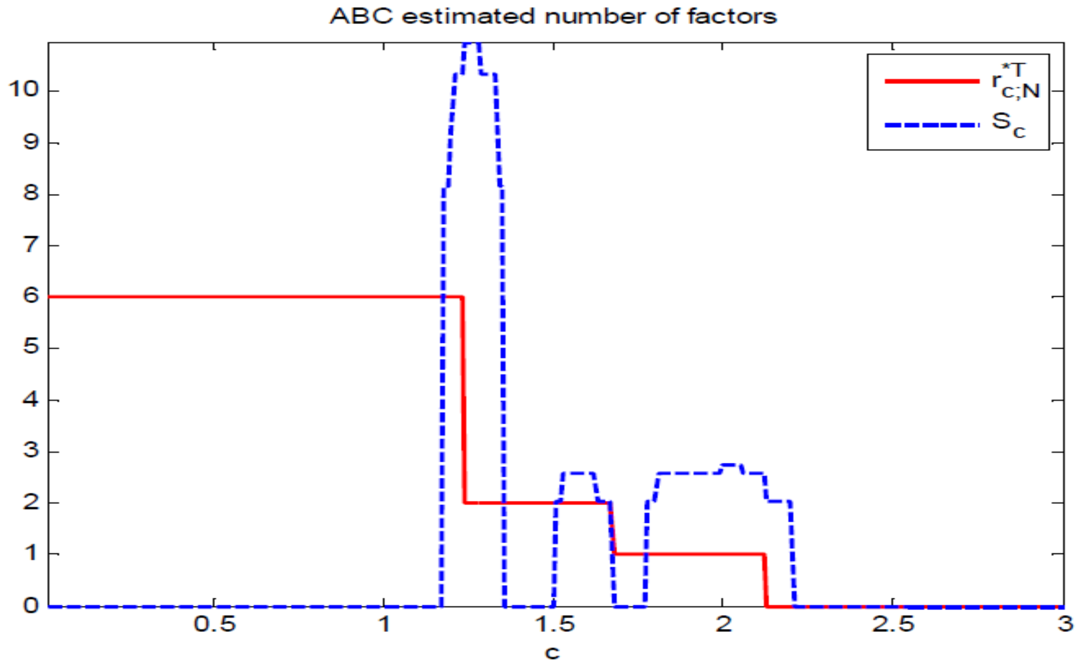
The only information available regarding the behaviour of $\hat{r}^{T}_{c,N}$ can be gleaned from analysing subsamples of sizes (n_j, t_j). For any j, we can compute $\hat{r}^{t_j}_{c,n_j}$ which is a monotonic non-increasing function in c. Therefore, there exist moderate values of c such that $\hat{r}^{T}_{c,N}$ converges from above to r. This result, however, needs to be independent of j for the criterion to be stable. This is measured by the variance of $\hat{r}^{t_j}_{c,n_j}$ as a function of j:

[9] See Alessi et al. (2010) for the functional form of the penalty function.

$$S_c = \frac{1}{J}\sum_{j=1}^{J}[\hat{r}_{c,n_j}^{t_j} - \frac{1}{J}\sum_{j=1}^{J}\hat{r}_{c,n_j}^{t_j}]^2 \tag{9}$$

Figure 3 shows the estimated number of factors for our model. The vertical axis represents the number of factors while the horizontal axis represents an arbitrary positive real number c. We run the results over a number of sizes for the subsamples in order to get a robust result. In order to determine the number of factors we have to find the first value of $\hat{r}_{c,n_j}^{t_j}$ where S_c is zero. The results suggest that the number of factors should be two.

Figure 3: ABC criterion for common factors



The other important choice that is required in the model is the number of common shocks, l, included. As we only use two common factors, we can easily assume that one common shock will be sufficient. This is based on arguments made by Forni et al. (2005) and Bai and Ng (2007) that the number of common shocks (l) is less than the number of common factors (r). This argument follows as economic fluctuations are driven by a small number of common shocks. However we test the number of common shocks using the information criterion specified by Onatski (2009). We test the null hypothesis of $l = l_0$ shocks versus the alternative hypothesis of $l_0 < l \leq l_1$ shocks. The test (Table 3) supports the arguments made by Forni et al. (2005) and Bai and Ng (2007), determining a common shock of one.

Table 3: Number of dynamic factors

Null Hypothesis	p-value	Decision	Alternative
$H_0 : l = 1$	0.327	Do not Reject null	$H_1 : 1 < l \leq 2$
$H_0 : l = 2$	0.571	Do not Reject null	$H_1 : 2 < l \leq 3$
$H_0 : l = 3$	0.820	Do not Reject null	$H_1 : 3 < l \leq 4$

The rationale behind factor analysis is that the dynamics in all these variables can easily be captured by few common factors. In so doing, the model mimics closely information taken into account by policymakers, who do not base their decision from observing a single variable. It is clear in Figure 4 that Factor 1 tracks the GDP growth quite well. Moreover, the correlation between GDP growth and Factor 1 is 0.80, which is far above most correlations in Table 2.

Figure 4: Factor 1 and GDP growth

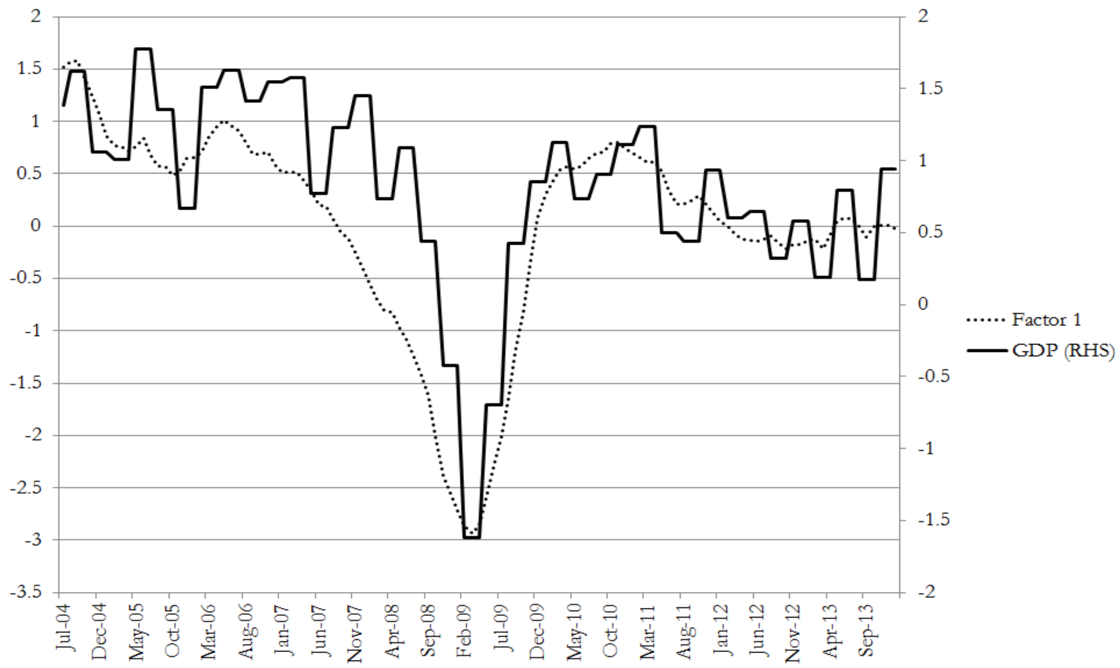
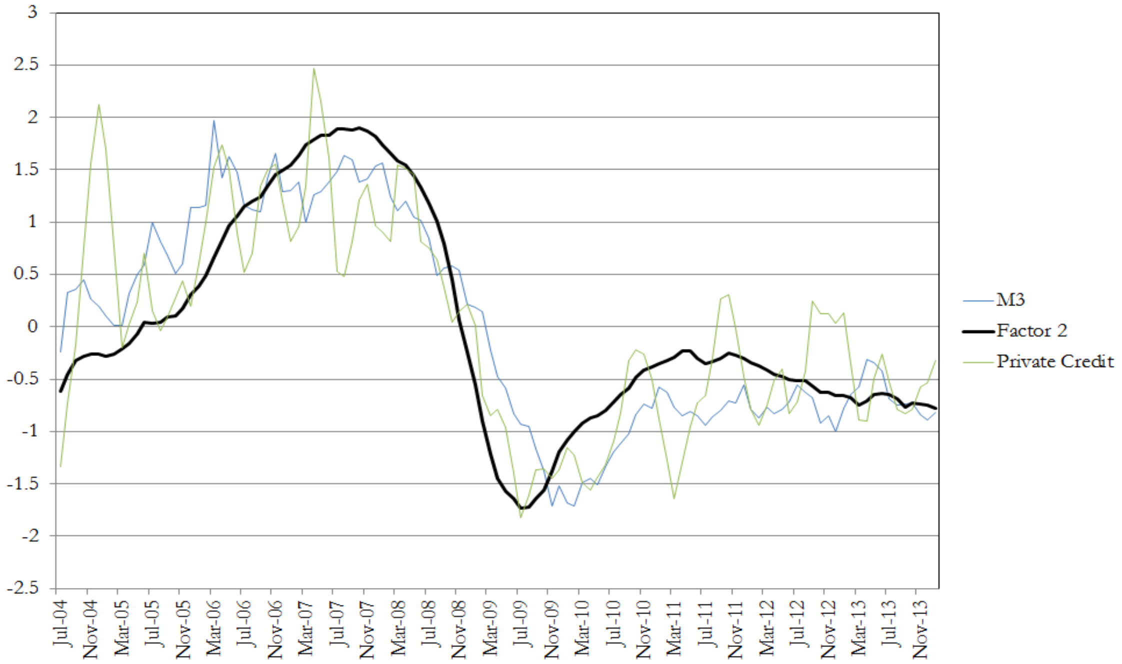


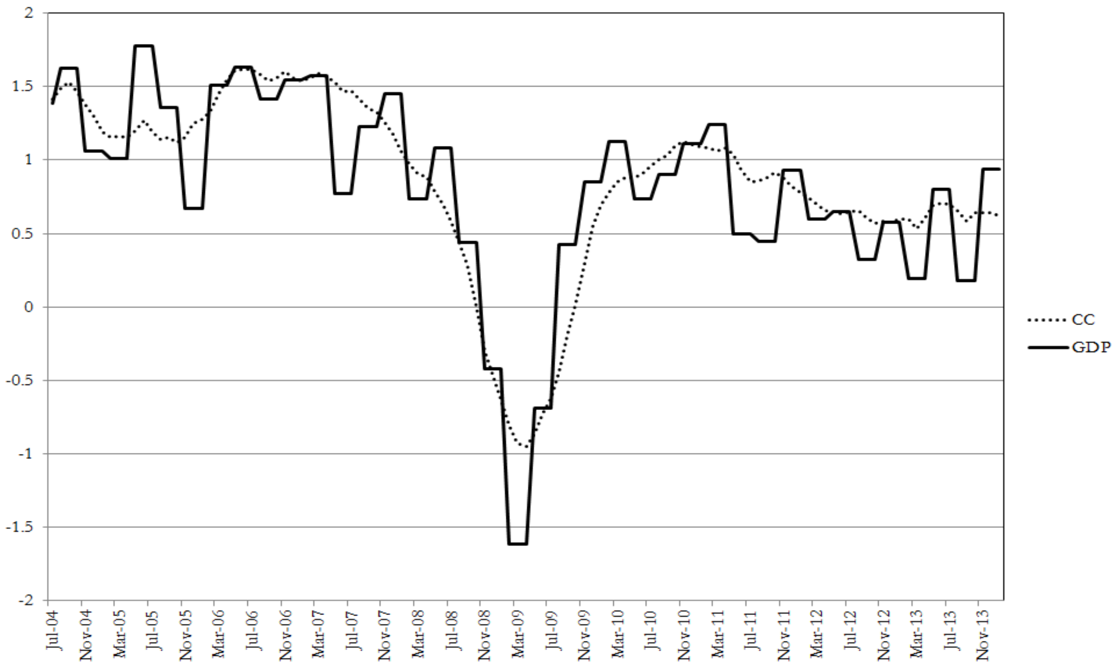
Figure 5: Factor 2, M3, and Credit to Private Sector



Factor 1 represents the real sector, while Factor 2 is closely linked with M3 money supply and the credit to private sector.[10] We can then aggregate the two factors into a single index, the common component, as depicted in Figure 6, as a proxy of monthly GDP growth rather than using the growth in manufacturing production. The constructed series follows GDP growth much better than the Factor. The nowcasting model allows us to update our nowcast of GDP growth with each new release. In addition, it is possible to evaluate the contribution of each variable in predicting GDP growth.

[10] See Factor 2 in Figure 5.

Figure 6: Common component and GDP growth



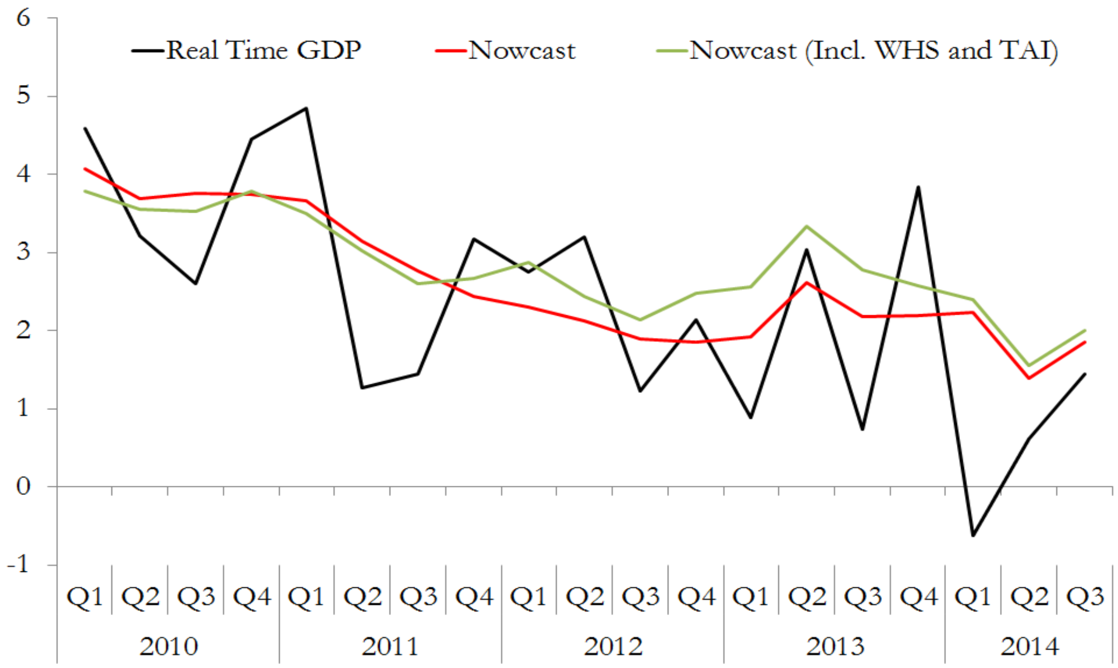
6.2 Forecasting results

We compare our nowcasting model to both survey results as well as real-time benchmark models. These models include:

- a random walk model (labelled RW);
- two autoregressive models with one and four lags (labelled AR(1) and AR(4));
- two four variable vector autoregressive models with one and four lags (labelled VAR(1) and VAR(4)). These models include consumer price inflation, the repurchase rate and the nominal effective exchange rate;
- a FAVAR model including two unobserved common factors and four observed variables included in VAR(1) and VAR(4);
- and a LBVAR model including all 17 variables included in the FAVAR model.

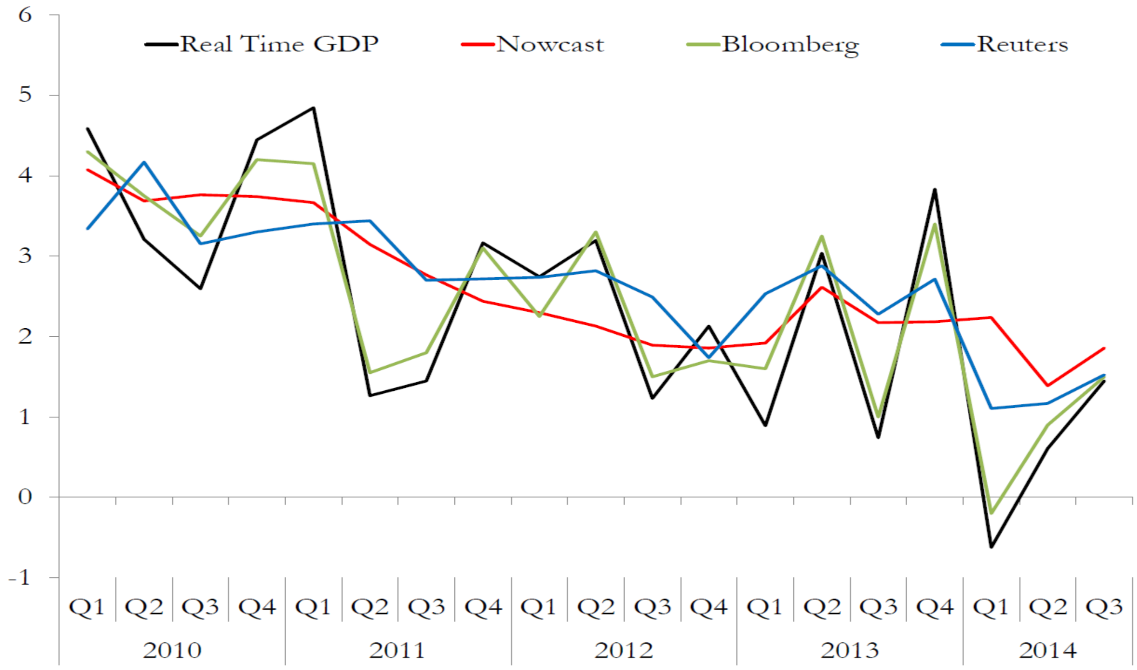
Contrary to most nowcasting models in the literature which include manufacturing production, we exclude this variable as it affects the forecasting bias. Wholesale trade and trade activity index portray similar effects in predicting GDP growth in South Africa. Figure 7 illustrates the negative impacts of the wholesale sale trade and the trade activity index rendering the forecast biased upward. By including these variables the model performs well in predicting the peaks, whereas it falls short in predicting the troughs. Hence, we decide to remove them from the analysis.

Figure 7: Model with and without Wholesale Trade and Trade Activity Index



Note from Figure 7 that the GDP growth recorded in the out-of-sample period is less stable. Figure 8 represents the results based on nowcasting and the results of the professional forecasters based on the surveys conducted by Reuters and Bloomberg. The results, based on forecasts made by Reuters, show an upward biased in forecasting. In general they tend to predict relatively well the peaks, but they miss the troughs. Nevertheless it is worth mentioning the difficulty faced by forecasters in predicting turning points. However, forecasts by Bloomberg follow closely the real-time GDP growth.

Figure 8: Nowcast vs Professional Forecasters



Figures 9 and 10 depict out-of-sample forecasts of alternative models, namely, AR(1), VAR(1), FAVAR, and LBVAR. All these models forecasts GDP growth with one lag. They display the same pattern since 2013Q1. Interestingly, they all miss the contraction of first quarter of 2014 by a considerable amount. We attribute the superiority of the nowcast model to the benefit it incurs from real-time flow of information. Even though it uses relatively the same number of variables as the large-scale models, it outperforms them by far.

Figure 9: Nowcast vs AR(1) and VAR(1)

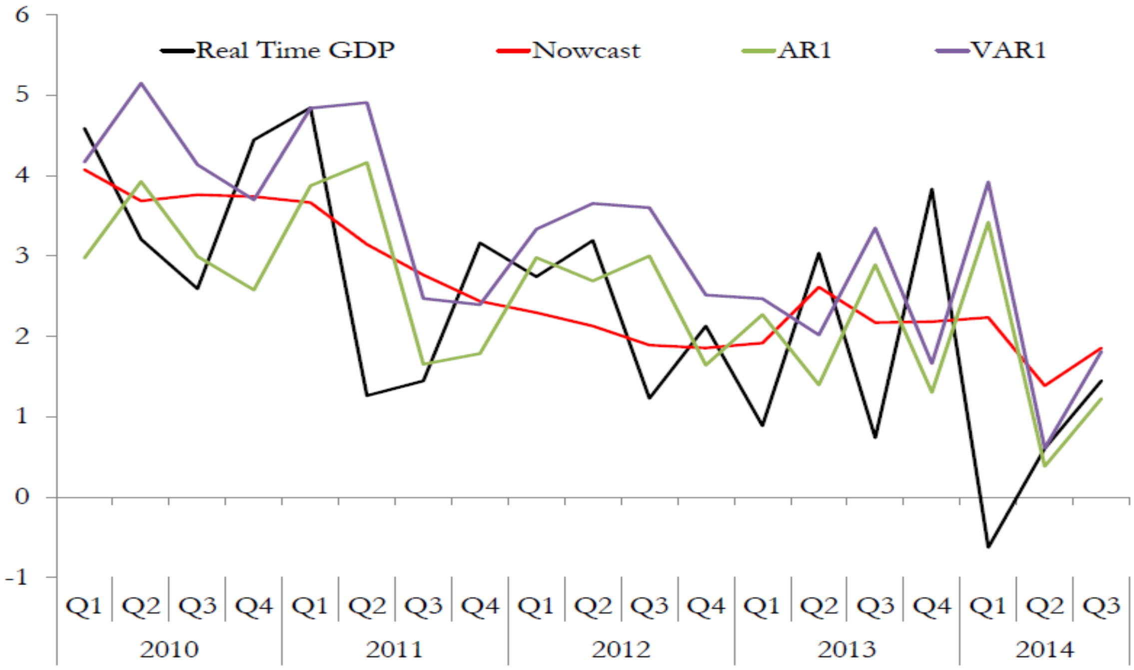


Figure 10: Nowcast vs FAVAR and LBVAR

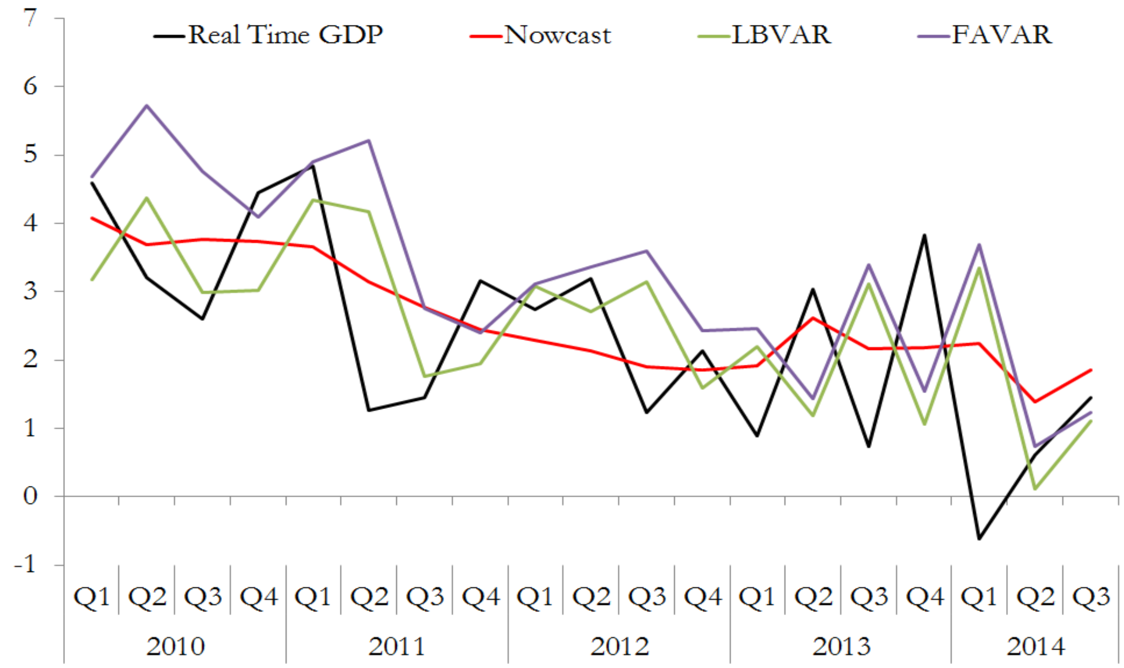


Table 4 compares the out-of-sample Root Mean Squared Forecast Errors (RMSFEs) of the nowcast model, the two surveys, as well as the benchmark models. The results show that both survey outcomes do better than the nowcast model with the lowest RMSFE of 0.406 by the Bloomberg survey. The results confirm the observation in Figure

8. But the superiority of Bloomberg forecasts can be attributed to its timeliness. Recall that Bloomberg forecasts are published two days before the release of GDP. Hence, these forecasters benefit from most recent information which are unavailable to the nowcast model used and the Reuters survey. The latter's results are marginally better than the nowcast model with a RMSFE of 1.129 versus 1.145. Importantly, however, this result is driven by one outlier in 2014Q1. If we exclude this datapoint, the nowcast model outperforms the Reuters survey. This is despite the fact that these surveys incorporate judgement, a luxury the nowcast model does not have. In addition, it is evident from Table 4 that the nowcast model outperforms all benchmark models even the large scale models which are known to do well given the advantage they possess in accommodating many variables and thus solving the problem of overparameterisation common with traditional VARs.

Table 4: Out-of-sample Root Mean Squared Forecast Errors

		Nowcast	Bloomberg	Reuters	LBVAR	FAVAR	AR(1)	AR(4)	VAR(1)	VAR(4)	RW
2010	Q1	0.265	0.084	1.567	2.014	0.009	2.605	4.961	0.177	2.274	1.957
	Q2	0.227	0.292	0.921	1.341	6.368	0.515	0.224	3.766	2.371	1.904
	Q3	1.366	0.430	0.312	0.156	4.715	0.162	0.022	2.379	6.500	0.379
	Q4	0.497	0.060	1.311	2.049	0.125	3.483	3.929	0.557	0.263	3.427
2011	Q1	1.392	0.483	2.087	0.256	0.004	0.940	0.510	0.000	0.514	0.160
	Q2	3.537	0.082	4.734	8.489	15.591	8.400	8.510	13.288	16.837	12.820
	Q3	1.739	0.124	1.566	0.095	1.718	0.043	0.016	1.050	5.409	0.034
	Q4	0.527	0.004	0.201	1.469	0.582	1.894	1.406	0.592	0.195	2.947
2012	Q1	0.200	0.244	0.000	0.120	0.134	0.056	0.408	0.349	0.186	0.177
	Q2	1.130	0.011	0.140	0.236	0.031	0.252	0.404	0.211	0.028	0.202
	Q3	0.440	0.073	1.590	3.659	5.584	3.140	3.084	5.624	2.614	3.854
	Q4	0.075	0.186	0.154	0.299	0.092	0.236	0.370	0.148	2.144	0.810
2013	Q1	1.058	0.503	2.692	1.711	2.456	1.907	2.219	2.496	4.702	1.537
	Q2	0.179	0.045	0.025	3.452	2.574	2.687	2.359	1.034	0.467	4.609
	Q3	2.047	0.066	2.357	5.657	7.069	4.624	5.254	6.801	3.801	5.270
	Q4	2.719	0.189	1.256	7.658	5.219	6.393	6.425	4.707	3.071	9.562
2014	Q1	8.179	0.178	2.989	15.823	18.600	16.355	15.872	20.660	19.966	19.863
	Q2	0.608	0.085	0.316	0.251	0.016	0.049	0.006	0.000	0.162	1.513
	Q3	0.166	0.003	0.006	0.120	0.048	0.049	0.400	0.133	1.451	0.708
RMSFE (excl. 2014Q1)		**1.005**	**0.406**	**1.086**	**1.473**	**1.705**	**1.442**	**1.500**	**1.551**	**1.716**	**1.698**
RMSFE		**1.178**	**0.407**	**1.129**	**1.699**	**1.932**	**1.683**	**1.723**	**1.835**	**1.960**	**1.943**
Relative to RW		**0.606**	**0.209**	**0.581**	**0.874**	**0.994**	**0.866**	**0.887**	**0.944**	**1.008**	**1.000**

7 Conclusion

Real GDP growth is the single most relevant variable describing the path of the economy and is used, together with inflation, to substantiate the direction of the monetary policy. Unfortunately, the GDP figure is released with a significant lag, usually between six to eight weeks after the end of the relevant quarter. The proposed framework allows us to overcome this problem by exploiting valuable high frequency data to forecast real GDP.

The framework uses a dynamic factor model to summarise this dataset providing a nowcast of current quarter growth from 2010 to 2014. Furthermore it provides a mechanism to determine the marginal impact of new data releases on real GDP growth. The benefit of this marginal impact or news is that a forecaster can quantify the evolution of economic activity in real time. Also it provides policymakers with the likely meaning of a large number of economic series on the path of real economic activity.

Given the relatively short period of real-time data, the results should be interpreted with caution with further monitoring required. Nevertheless, the results shows that this model performs comparatively well against consensus forecasts of quarterly growth by Reuters. This is despite the model not incorporating judgement as is the case in the Reuters survey. A pertinent example in South Africa occurred in the first quarter of 2014 when a prolonged strike in the platinum sector resulted in a contraction in real GDP growth, something that survey participants could adjust for but that wasn't fully captured in the data. Encouragingly, if you remove this data point, the nowcast model outperforms the survey. The nowcast model also outperforms all other benchmark models by a significant margin.

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